Modeling the Determinants of Large-Scale Building Water Use: Implications for Data-Driven Urban Sustainability Policy

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KEYWORDS: urban water consumption, determinant analysis, water efficiency, urban policy; urban sustainability

ABSTRACT:

As the world's population continues to urbanize, cities are struggling to meet the demand for key resources such as clean water. In urban areas, enhancing the sustainability and water efficiency of buildings is crucial to meeting the resource needs of a growing population. Nevertheless, an understanding of the determinants of urban water consumption - and specifically of multi-family residential buildings that constitute the bulk of the urban building stock - has been limited. Using an extensive database of actual water use from New York City's Local Law 84, coupled with land use and demographic data from the NYC Primary Land Use Tax Lot Output (PLUTO) database and Census data, we apply weighted robust regression and geographically weighted regression (GWR) models to analyze the determinants and spatial patterns of water consumption in over 2,300 multi-family buildings located in New York City. Our results indicate that occupancy, building size, building age, ownership structure, neighborhood demographic and socioeconomic characteristics, and the energy use intensity (EUI) of a building all have statistically significant effects on the water use intensity (WUI) of multi-family housing. Results of the GWR spatial analysis demonstrate large spatial variability across building characteristics, demographic variables and household income. The analysis and findings presented here give further support to the potential of targeted measures and incentives, segmented and classified by building characteristics and neighborhoods, may be effective tools for policymakers seeking to increase water efficiency in urban buildings and to accelerate reductions in resource use at the city scale.

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INTRODUCTION

As the well-documented urbanization of the world's population continues, the influx of people to urban centers has intensified the strain on key resources such as clean water (UNDESA 2011). Meeting this increased need will be a daunting challenge, with only 60 percent of global demand for potable water expected to be satisfied in 2030 (Boccaletti, Grobblel, and Stuchtey 2010). Despite having substantial natural water resources, the United States is facing significant water shortages, especially in the western states, and current water conservation projects are not expected to meet goals set by the United States Environmental Protection Agency (EPA) (Christen 2003; Lee, Tansel, and Balbin 2011). Taking into account the impact of climate change effects over time, a large portion of the United States is projected to be at high risk of failing to meet water demand by 2050 (Roy et al. 2012).

Increasing water efficiency of the urban built environment offers significant opportunities to reduce overall water usage and meet the conservation targets necessary to enhance the long-term sustainability of our cities. Buildings are increasingly becoming major contributors of water consumption in United States, with residential and commercial buildings accounting for over 95% of all consumption growth from 1985 to 2005 (U.S. DOE Building Energy Data Book). The growth in urban population has led to a commensurate increase in the population living in multi-family housing. According to data from the 2009 U.S. Residential Energy Consumption Survey, approximately 17 percent of the 119 million residential buildings in the U.S. consist of multi-family structures with five or more units, and 43 percent of households live in such structures. Of these, fully 97 percent are located in urban areas (U.S. Department of Energy, Residential

Energy Consumption Survey 2009). Of particular importance, almost 88 percent of those that live in multi-family housing are renters, and are more likely to be poor, minority households. Nationally, according to data from the National Multi-Housing Council, 63 percent of households in multi-family rental housing earn less than \$35,000, with a median income of just \$25,768 compared to \$45,964 for all U.S. households (National Multi-Housing Council 2014). In New York City, which has the highest population density in the country, multi-family buildings account for over two-thirds of the total housing units and represent a large majority of potable water consumption.

Burdened by ageing and strained infrastructure, many cities now face significant challenges in both providing an adequate supply of potable water to meet demand and processing wastewater outflows (American Society of Civil Engineers 2013). In New York, for example, the Combined Sewer Overflow (CSO) system mixes stormwater and wastewater and, when flows exceed twice design capacity, this flow is diverted directly into the City's waterways. In this scenario, the wastewater is left untreated, creating significant impacts on water quality and public health (City of New York 2010). In addition to potential health impacts, the cost of water continues to increase. Between 2007 and 2014, the average annual rate increase was 10.2 percent in New York, reflecting a growing cost burden for lower-income households and raising the annual water cost for an average multi-family housing unit to \$666 per year.

Given the necessity to lower operating and capital costs of utility infrastructure and delivery, as well reduce carbon emissions to mitigate the effects of climate change, cities have been at the

forefront of establishing policies to increase the efficiency and overall sustainability of buildings, either through the adoption of green building standards or the passage of disclosure and reporting requirements (Fuerst, Kontokosta, and McAllister 2014; Kontokosta 2011). While energy consumption has been the primary focus of building efficiency programs, water efficiency has become a more prominent component of green building standards and building codes (Hoecker and Bracciano 2012). However, despite the identified cost and energy/water savings potential of installing more efficient systems and changing behavior, such efficiency and conservation measures have been relatively slow to proliferate throughout existing buildings, as opposed to new construction. Commonly cited reasons for not adopting such measures include capital cost and return on investment, uncertainty over actual savings realized, and unfamiliarity with available measures (Kontokosta 2013). Of course, these barriers vary by building sector and type; in the residential sector, differences in the motivations and constraints facing owners and renters in single-family homes and multi-family housing are substantial.

Using an extensive database of actual water use from New York City's Local Law 84, coupled with land use and demographic data from the NYC Primary Land Use Tax Lot Output (PLUTO) database and Census data, we apply weighted robust regression and geographically weighted regression models to analyze the determinants and spatial patterns of water consumption in over 2,300 multi-family buildings located in New York City. We aim to provide insight into the drivers of water consumption in multi-family buildings to inform policy measures designed at reducing and managing water consumption in buildings as part of broader sustainability agenda. Specifically, our research goals are to (1) understand the drivers of multi-family housing water consumption to develop building-level benchmarking and water performance measures, (2)

analyze patterns of use both spatially and by building type to identify opportunities to segment the multi-family housing stock, and (3) examine differences in consumption patterns and intensity by socioeconomic status of households and by neighborhood income and demographics. The next section explores relevant research in urban planning, water consumption, and water resource management, followed by a description of our data, methodology, and results. The paper concludes with a discussion of the implications of the results for policy and planning, limitations of the work, and future steps.

BACKGROUND

Urban water demand modeling has been extensively studied over the last several years as highlighted by House-Peters and Chang's (2011) comprehensive review paper. A substantial proportion of the literature has been focused on understanding the socioeconomic factors and physical building characteristics that impact single-family residential water use (Chang, Parandvash, and Shandas 2010; House-Peters, Pratt, and Chang 2010; Ouyang, Wentz, Ruddell, and Harlan 2013; Polebitski and Palmer 2009; Wentz and Gober 2007). Yet, despite building typology being shown to impact water usage in several studies, there is a dearth of research examining the socioeconomic factors and physical building characteristics that impact water usage in multi-family residential buildings in dense urban areas like New York City (Domene and Sauri 2006; Fox, McIntosh, and Jeffrey 2009; Wentz et al. 2014; Zhang and Brown 2005). Schleich and Hillenbrand (2009) conducted determinant analysis of water usage for several building types, but water consumption data was not available at the spatial granularities necessary to conduct building-by-building analysis. Similarly, Shandas and Parandvash (2010)

examined water consumption across building types, although detailed data on multi-family buildings was not available to conduct analyses specific to such buildings. Therefore, a primary contribution of this paper will be to extend previous research to encompass multi-family buildings and analyze actual building-level water use data.

Determinants of Water Consumption

Previous work has found household income (Grafton, Ward, To, and Kompas 2011; Guhathakurta and Gober 2007; Kenney et al 2008; Schleich and Hillenbrand 2009), household size (Arbues and Villanua 2006; Arbues, Villanua, and Barberan 2010; Campbell, Johnson, and Larson 2004; Domene and Sauri 2006; Grafton, Ward, To, and Kompas 2011; House-Peters, Pratt, and Chang 2010; Mazzanti and Montini 2006; Schleich and Hillenbrand 2009; Wentz and Gober 2007), age of household members (Fox, McIntosh, and Jeffrey 2009; Kenney et al. 2008; Schleich and Hillenbrand 2009), education level of household members (Arbues and Villanua 2006; House-Peters, Pratt, and Chang 2010; Shandas and Parandvash 2010) and race distribution (percent Hispanic) (Balling, Gober, and Jones 2008) to be key socioeconomic factors that impact residential water usage. Recent research has also found numerous physical building characteristics to impact water usage, including: building size (square footage) (Balling, Gober, and Jones 2008; Chang, Parandvash, and Shandas 2010; Domene and Sauri 2006; Harlen, Yabiku, Larsen, and Brazel 2009; Tinker, Bame, Burt, and Speed 2005; Wentz and Gober 2007), housing typology (Domene and Sauri 2006; Fox, McIntosh and Jeffrey 2009; Zhang and Brown 2005) and the number of bedrooms per unit or per house (Fox, McIntosh, and Jeffrey 2009; Kenney et al. 2008). The impact of socioeconomic and physical building variables has been

shown to substantially differ from one geographic region to another. For example, Schleich and Hillenbrand (2009) found in their study of residential usage in Germany that as income increases, water consumption disproportionately increases, while House-Peters et al. (2010) did not find income to be a significant driver of water usage in Hillsboro, a suburban city of Portland, Oregon. Consequently, conducting determinant analysis using localized water use data is essential to assess the applicability of previous models and conclusions to the local conditions of New York City, and potentially other large cities with significant proportions of multi-family housing.

Previous research has also begun to highlight the impact local spatial proximity plays in urban water usage. Differences in neighborhood characteristics have been shown to influence water consumption patterns, perhaps by capturing (unobserved) effects of localized climate conditions, neighborhood socioeconomic and cultural differences, and variations in the provision of water infrastructure and maintenance. Several studies have conducted spatial analysis of water use at the census block group level (Breyer, Chang, and Parandvash 2012; Chang, Parandvash, and Shandas 2010; House-Peters, Pratt, and Chang 2010; Lee, Chang, and Gober 2015) and at the census tract scale (Balling, Gober, and Jones 2008; Guhathakurta and Gober 2007; Lee, Wentz, and Gober 2009; Wentz and Gober 2007). Chang et al. (2010) found that spatial regression and geographically weighted regression (GWR) may be better suited to account for variability in water usage across an urban area than typical ordinary least squares (OLS) models. For example, OLS models were shown to overestimate the influence of key determinants such as building size and age in Portland, Oregon (2010). Moreover, GWR analysis allowed Wentz and Gober (2007) to examine the sensitivity of water usage relative to household size across census tracts. Results

of the GWR analysis illustrated that household size has little effect on residential water consumption in the affluent neighborhoods of Phoenix, Arizona, implying that the primary drivers of water use in this demographic are likely to be associated with dishwashers, showers, toilets and clothes washers (Wentz and Gober 2007). Spatial analysis has also been utilized by Guhathakurta and Gober (2007) to assess the impact of the urban heat island on water usage across census tracts in Phoenix, Arizona. In order to fully inform municipal policy regarding water efficiency, we extend our analysis of water consumption beyond the building scale to incorporate spatial differentials using a geographically weighted regression (GWR) model for buildings and neighborhoods across New York City.

Intersection of Water and Energy Efficiency

The link between water and energy (i.e. “water-energy nexus”) is garnering substantial interest from the research community. The power generation sector consumes nearly twice as much water as the next biggest sector in the United States (Blackhurst, Hendrickson, and Vidal 2010) and drinking water supply and distribution have also been shown to require significant amount of energy, highlighting the importance of simultaneously understanding energy and water usage (Mo et al. 2010). Recent work also illustrated the merits of conveying this linkage between energy and water usage to engender efficient behavior (Jeong 2014). Moreover, a recent analysis by Zhou et al. (2013) illustrated the potential for reducing energy usage and greenhouse gas emissions through increased water efficiency. This analysis found that reducing urban water consumption by 1 Mt in the residential sector would yield a reduction of .4 Mt coal equivalent in energy savings. Significant amount of research has studied the determinants of water usage in

certain sectors (as highlighted earlier) or energy usage (Cayla, Maizi, and Marchand 2011; Ekholm, Krey, Pachauri, and Riahi 2010; Kavousian, Rajagopal, and Fischer 2013; Kontokosta 2014; Sutterlin, Brunner, and Siegrist 2011), but very little research has examined the correlation between water efficiency and energy efficiency in the building sector. As part of our analysis, we explore if a relationship exists between the water usage and energy usage of buildings and if such a relationship could be leveraged for coupled energy and water efficiency policy measures.

DATA AND METHODOLOGY

Data

Our water consumption, energy use, and building attribute data come from New York City's Local Law 84 (LL84), one of the first building energy disclosure policies adopted in the United States (Burr, Keicher, and Leipziger 2011). This policy requires buildings over 50,000 square feet, or tax lots with more than 100,000 square feet of combined building area, to report energy and water use data each year. New York City's disclosure policy is reflective of a shift among cities to utilize – and generate – new streams of information to improve the measurement and benchmarking of resource flows through the built environment (Kontokosta 2013). This analysis specifically uses LL84 water use data for calendar year 2012 and merges these data with parcel-level information and additional building attribute data from New York City's Primary Land Use Tax Output (PLUTO) database. The PLUTO database contains land use and geographic data for every tax lot in New York City, aggregating information from multiple New York City agencies including the Department of City Planning and the Department of Finance. Data cleaning steps

included dropping duplicate observations and water use outliers below the 1st percentile and above the 99th percentile of the water use intensity distribution.

In total, the cleaned water use data from LL84 multi-family buildings accounts for 24.9 billion gallons of consumption per year across a total 4,893 properties with submitted water data. The mean and median consumption per unit are 69,028 gallons per year and 57,271 gallons per year, respectively. As shown in Figure 1, the distribution of consumption, however, exhibits rather significant variability, with the top decile of building water use intensity fully 4.6 times larger than the bottom decile. Estimates of per person consumption in multi-family buildings range (bottom/top decile) from 31 gallons per day to 144 gallons per day. Figure 2 presents a visualization of the spatial variation in water use intensity across the sample.

[INSERT FIGURE 1 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

The final step in building the dataset used for this analysis consists of merging the LL84 and PLUTO data with neighborhood socioeconomic and demographic data from the 2010 U.S. Census and the 2006-2010 (five-year estimate) American Community Survey (ACS). These data are collected at the census block group level, a statistical division of census tracts and the lowest level of geographic aggregation available given sampling errors present in the ACS data and

privacy concerns regarding personally identifiable information (U.S. Census 1994). The resultant final merged, cleaned dataset encompasses complete records for 2,307 properties.

Modeling the Determinants of Water Use Intensity

We estimate the determinants of water use intensity (WUI) in multi-family residential buildings using two modeling approaches. The first involves a linear multi-variate regression model with robust standard errors, weighted by the proportion of coverage of our building water use data by census block group. This approach allows for an understanding of the magnitude and significance individual building, occupant, and neighborhood factors that influence water use intensity. The second algorithm employed uses a geographically weighted regression model to study the localized spatial variation in water use intensity, and the geographic-varying effects of individual explanatory factors. Both approaches are described in detail below.

Weighted Robust Multivariate Regression

Our first analytic approach examines the drivers of water use intensity of multi-family residential buildings using multivariate linear regression models with Huber-White robust standard errors (White 1980). Robust standard errors help to account for heteroscedastic residuals, although we check the presence of possible model misspecification using an additional test of the divergence between robust and classical standard error differences (King and Roberts 2012). We begin by estimating a semi-logarithmic regression models with robust standard errors. The log transform allows for the interpretation of independent variables on the elasticity of the water use intensity,

where a unit change in the independent variable results in a corresponding percentage change in the dependent variable. The primary model specification is given by:

$$\log y = \alpha + \beta BLDG + \gamma OCC + \delta SE + \epsilon$$

where y is the log of the water use intensity for property i ; $BLDG$ is a set of property-specific construction and design characteristics; OCC is a set of occupancy and unit amenity characteristics; SE is a set of locally-proximate socioeconomic characteristics, and β, γ, δ are vectors of coefficients to be estimated. Dummy variables are also included for building type classification as determined by the New York City Department of Finance. Definitions and sources of the data is provided in Table 1.

[INSERT TABLE 1 ABOUT HERE]

To estimate the effects of socioeconomic and demographic characteristics on building-level water consumption, we collect U.S. Census data for the 710 census block groups in New York City's five boroughs that contained buildings for which we obtained water use data. In the case of New York City, each census tract consists of two to six block groups and each block group contains a population of approximately 600 to 3,000 persons.

The estimation challenge here is merging our data of property-specific water consumption information and other characteristics with local neighborhood (block group) socioeconomic data to approximate property-specific socioeconomic conditions. Our approach is as follows:

A given block group i contains some number n of individual properties j with water and other building attribute data obtained through Local Law 84 and PLUTO. Each property j contains some number of buildings with an aggregate size X given in square feet. We estimate the proportion of our water use and property-specific data coverage of the total multi-family building area in census block group i as:

$$\phi_i = \left(\sum_{j=1}^n x_j \right) / X_i$$

To account for spatial variations in the water use data coverage across block groups, we estimate a weighted regression model using the above coverage proportion as an analytic weight in the robust estimation with clustered errors. This approach is necessary to control for potential bias in the neighborhood (block group) variable coefficient estimates resulting from the variance in actual water use and property-level data within individual block groups.

Geographically Weighted Regression

Previous research has highlighted that water usage can exhibit high spatial heterogeneity in urban areas (Chang, Parandvash, and Shandas 2010). In order to ascertain the spatial variations in our water usage data, we created a geographically weighted regression (GWR) model. A GWR model builds on traditional linear regression modeling by allowing the linear predictor to

vary for each observation for each observation (i) in the dataset with geographic coordinates (u_i, v_i) (Fotheringham, Brunson, and Charlton 2002):

$$y_i = \alpha(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_k(u_i, v_i) + \varepsilon_i$$

Each regression estimates a set of coefficients and an intercept from the values of the dependent and independent variables for that observation at a given location (u, v) and weighted values of nearby observations. We utilize the “spgwr” software package (Bivand, Roger, et al. 2014) for R, a software environment for statistical computing and graphics, for GWR based analysis. We select an adaptive Gaussian kernel in the GWR software package to sample the nearby observations. The GWR provides coefficients, standard errors and r^2 values for each observation and a quasi-global r^2 value. Our main goals are to understand how determinant coefficients vary across the geographic region of New York City and to determine if the GWR provides a better explanation of the variations in water consumption than a standard OLS model by applying the significance test detailed in Brunson, Fotheringham, and Charlton (1999).

RESULTS

The coefficient estimates for the non-weighted model and the weighted regression model are presented in Tables 2, respectively, and the geographic weighted model coefficients are presented in Table 3. The results indicate statistically significant coefficients for a range of unit, property, and neighborhood-level variables. Both models explain approximately 25 percent of the variation in building water use intensity, with modest improved explanatory power exhibited in the geographically weighted regression output.

[INSERT TABLE 2 ABOUT HERE]

Results of Weighted Robust Regression Model

As expected, unit occupancy is positively correlated with water consumption. For every additional person added per housing unit, controlling for other factors, the building's WUI increases by approximately 18 percent. For context, the mean water consumption per unit in New York City's multi-family buildings is approximately 69,028 gallons per year, and each additional person in a multi-family housing unit above the mean unit occupancy of 2.5 persons would increase per unit consumption, on average, by 12,425 gallons.

Larger buildings, measured by gross floor area, are found to have lower WUIs, although the number of floors of the structure does not influence water use. For every ten percent of additional floor area, WUI decreases by approximately 0.8 percent, suggesting greater efficiency in consumption as building size increases. This may be a function of better management in larger buildings or more efficient systems, although further analysis is needed to fully understand this relationship. We also find that buildings with dishwashers in most or all of the units do not have statistically significant differences in water consumption compared to buildings without dishwashers. This provides some additional empirical evidence to the debate over the relative water efficiency of using dishwashers versus hand washing of dishes (Richter 2010). The question here has revolved around the human behavior aspect of water use for dishwashing (for

instance, some may leave the water running while drying dishes) and the variation of water efficiency of dishwasher models.

Buildings built during the decades of the 1910s and 1920s, and the post-World War II decades of the 1950s and 1960s, have greater water use per square foot than those built prior to 1910. Newer buildings – those constructed in the last twenty years – demonstrate no statistically significant difference in water use per square foot. Here, the nature and age of the plumbing fixtures may be a contributing factor, as well as the condition of plumbing risers and supply lines (e.g. presence and propensity of leaks). A standard toilet, for instance, uses between 3.5 and 7.0 gallons of water per flush; a ‘low-flow’ version, common in more recent construction (and New York City Plumbing Code standard for new construction and major renovations as per Local Law 57 of 2010) will use 1.6 gallons, or less, per flush. Variations in the quality and condition of installed fixtures can have significant implications for water use intensity.

Buildings in neighborhoods with a greater proportion of renter-occupied units have far larger water use intensity than similar-owner occupied structures. Water use intensity increases by four percent with a ten percent increase in the proportion of renter-occupied units in the census block group. At the building level, we find a negative and statistically significant coefficient for the *Coop* (cooperative building) variable. Cooperatives are a form of ownership in which unit owners in a multi-family buildings own shares in the corporation that owns the underlying asset, thus creating a shared cost and risk structure. This finding for ownership and rental buildings may be explained, in part, by the differences in management quality and condition of rental

buildings when compared to ownership buildings (Galster 1983). It may be argued that overall building management and maintenance may be less proactive and responsive to leaks and other conditions that may negatively affect water consumption in rental buildings, where incentive exists to maintain the building at the minimum level necessary to avoid an implicit discount of rental rate or occupancy rate. In addition, occupants in rental buildings may have a dis-incentive to be concerned with their individual water consumption give the principal-agent (“split incentive”) problem that exists, as the building owner typically pays for water in such buildings (Bird and Hernandez 2012; Gillingham, Harding, and Rapson 2012).

We find both household income (measured as median household income in the block group) and the property’s assessed value per square foot³ of building area have negative and statistically significant coefficients. Thus, higher income households and higher value buildings tend to use less water per square foot. Furthermore, we find no statistically significant difference in water use intensity in subsidized housing (as defined by the variable included in the LL84 data) as compared to market-rate housing, after accounting for the assessed value of the building. The reason for these findings is unclear. First, higher-income households may have more floor area per person than lower-income households, thus reflecting a lower per square foot measure of water use as opposed to per capita measures. Since exact occupancy characteristics are not available for our study, we are unable to ascertain precise per capita water use measures to

³ The assessed value of a building provides a rough proxy of its market value; however, given the nature of the property tax system in New York City, variations in levels of assessments across tax classes, and caps on assessment increases over time, the assessed value differential is capturing both differences in market value and differences in property type.

explore this possibility further. Second, higher value buildings may be better maintained, with newer – and presumably more efficient – plumbing fixtures and fewer persistent water leaks.

Of particular interest is the positive, statistically significant relationship between WUI and Energy Use Intensity (EUI; is defined as energy consumption (BTU) divided by the square footage of a building ft²). Every ten percent increase in energy consumption is associated with a 2.8 percent increase in water consumption. It should be noted that while this finding indicates that higher energy consumption buildings also tend to have higher water consumption, it does not provide evidence of a link between poor building energy performance and water inefficiency. Effective resource use performance measures must normalize and account for a wide range of variables that EUI, alone, does not provide (Kontokosta 2014; Perez-Lombard, Ortiz, Gonzalez, and Maestre 2009).

Interestingly, the coefficients for the demographic variables included in the model are not statistically significant, with the exception of the percentage Black population in a given census block group. This result could be a function of the varying proportion of water use and building-specific data within and across the census block groups analyzed or potential differences in building conditions and property management across neighborhoods reflected in variations in socioeconomic and demographic composition. We utilize a GWR below to explore these neighborhood variations at a more granular spatial resolution.

Results of the Geographically Weighted Regression Model

Analysis of the coefficient of determination for the geographically weighted regression (GWR) model confirms that significant spatial heterogeneity exists across our study area and justifies the need for the GWR model to account for such heterogeneity, as shown in Figure 3. The full results of the GWR model are provided in Table 3. The GWR model resulted in an improvement of 36.502 on the SS residuals as compared to a standard OLS regression and is significant at the 5% level. Additionally, a reduction in the Akaike Information Criterion (AIC) from the OLS regression (4039.20 to the GWR model (3953.38) suggests the GWR model performs better (Fotheringham, Brunson, and Charlton 2002):. This result is consistent with the improved quasi-global coefficient of determination (r^2) of .267 returned by the GWR model.

[INSERT TABLE 3 ABOUT HERE]

[INSERT FIGURE 3 ABOUT HERE]

It is apparent from Table 3 that a number of the variables exhibit spatial variation across the study area. In an effort to derive the policy implications from the results, we highlight the following variables with high spatial variability and map the results in Figure 4: *Person per Household Occupied*, *Median Household Income*, *Percent Population Female*, *Percent Population Seniors*, *Percent of Space Non-Multifamily* and *Percent Renter Occupied*. An inverse spatial relationship exists for the number of person per household occupied. Adding a person in

the dense areas of lower Manhattan (light blue) has nearly half the impact on water consumption than adding a person in northern Manhattan or the Bronx (dark blue). It can be seen that Median Household Income has the most impact (negative) on water consumption in the center of the city (light blue) where density is high. Examination of the demographic variables also shows some interesting spatial patterns. Female population has an inverse relationship with water consumption (i.e. an increase in percent female population equates to a decrease in water consumption) in the central part of the city (light blue), but has a direct (positive) relationship in the outer boroughs of the city (dark blue). The impact of more senior citizens in the population is highly spatially variable with the dark areas on the map (lower Manhattan, Bronx, Staten Island) having a substantially stronger direct relationship on water consumption than the light blue areas (center part of Manhattan). The percent of renters in a building impacts water consumption more drastically in the dense areas of upper and lower Manhattan (dark blue). The impact of the percent of non-residential space in a multi-family building was also shown to vary significantly across the study area.

[INSERT FIGURE 4 ABOUT HERE]

DISCUSSION AND POLICY IMPLICATIONS

Domestic (potable) water has become an increasingly scarce and cost-intensive resource in many cities. New York City consumes approximately one billion gallons of water each day, and is investing over \$7 billion in new water supply infrastructure to accommodate current and future demand (City of New York 2013a). As urban policymakers seek strategies to reduce resource

consumption – driven by climate change, sustainability goals, or fiscal considerations relating to infrastructure investment and maintenance – understanding the determinants and spatial relationships of water use provide a critical starting place to effectively and optimally target policy interventions, incentives, and regulatory levers. The analysis presented here provides the first step in identifying the most significant occupancy, property, and neighborhood characteristics that impact water use. Many of our findings also suggest that behavior – either of residents or building managers – can be an important driver of water consumption. Spatial variations in consumption patterns suggest that different efficiency strategies – including education and public awareness campaigns – need to be tailored to differing conditions and drivers of water use across neighborhoods and building types.

Although the generalizability of our study needs to be explored further, our results suggest several strategies for cities and water agencies seeking to reduce water consumption in residential buildings. First, initially focusing initiatives on rental buildings could offer significant reduction potentials through enhanced management and maintenance oversight. Rental buildings are found to have significantly higher water use intensities than ownership buildings, even after accounting for differences in age, unit size, etc. Second, building age, at least in the case of New York City, provides some indication of relative water consumption and water efficiency, and provides an opportunity for targeting – and further studies – of the higher water use exhibited in buildings of certain vintages, controlling for other factors in our model, as discussed above. Finally, the correlation between water and energy use suggests that energy consumption data could be used to guide opportunities to reduce water use, and vice versa. The positive relationship between these two resources flows can be used to design programs, incentives, and

enforcement mechanisms that simultaneously address energy and water use, a step that would necessitate close coordination across the relevant city agencies. Examples include financial incentives for buildings that install systems to improve both energy and water efficiency, or targeted enforcement that audits energy consumption in buildings that have high water consumption profiles.

The results of the geographically weighted regression model can also be utilized to inform spatially targeted water efficiency programs. Spatial patterns of building characteristics (e.g. percent of space non-multifamily in a building) can be utilized as a basis to understand why specific building types in certain neighborhoods are associated with lower water consumption. For example, buildings with a greater proportion of non-residential uses in most of Manhattan are correlated with less water consumption, but the opposite is found in much of the Bronx. Spatial patterns highlighted in this study can also be utilized to inform where resources should be allocated for more specific and comprehensive research (e.g. the positive and negative correlations observed between percent female and water consumption in various parts of the city).

This work also provides an important foundational step in developing a water benchmarking rating for multi-family buildings. While the focus of benchmarking and performance rating programs has been on energy use, such as the U.S. EPA's Energy Star program, a similar approach could improve the understanding of relative building water performance and yield water use savings over time. Our analysis identifies the key drivers of water use in residential

buildings; these variables can be used as the normalization parameters in a benchmarking algorithm designed to match similar buildings and establish a multi-factor water performance rating. This rating system can be used to identify water efficient buildings and encourage market behavior change through awareness and recognition. Additional water data from a national sample of multi-family buildings could support the development of the requisite models.

LIMITATIONS

We identify three primary data and methodological limitations associated with our analysis. First, we are able to obtain water use data and associated building and neighborhood attributes for 2,307 of 10,548 the multifamily housing properties that reported energy use data as required by LL84 for the calendar year 2012, following our data cleaning procedures. While this represents a significant sample, particularly in relation to previous studies of urban building water consumption, it does not provide equal coverage across the five boroughs of New York City and, because of the requirements of LL84, generally does not include small- and medium-sized buildings less than 50,000 square feet. Such buildings are predominant in the boroughs other than Manhattan. In addition, while a majority of the water use data come from Automated Meter Reading (AMR) devices from the NYC Department of Environmental Protection, additional analysis is warranted to verify the accuracy, consistency, and coverage of data collected both by AMR and through self-reporting. Second, the approximation method used to match neighborhood (census block group) data to property-specific data provide only estimates of socioeconomic characteristics for the individual buildings for which we have water data. We attempt to account for this approximation using the weighting methodology described above.

Third, although we utilize a robust dataset of property-specific multi-family building water use, omitted variables may bias the coefficient estimates of the models. For instance, although we can assume number of bedrooms and unit size as proxies, additional details on number of bathrooms and number of plumbing fixtures could be useful information and add explanatory power to the models.

The data for this analysis represent an unprecedented range of building, occupant, and neighborhood attributes combined with actual water consumption. As with any market- or city-specific study, further testing and exploration is needed to understand the extent of the generalizability of our results, especially given the heterogeneity, scale, and age of the New York City building stock. However, based on lessons from building energy data and benchmarking analysis from multiple cities, common relationships characteristics and outcomes emerge that can serve as the basis for further comparative analyses (Washington DC District Department of the Environment 2014; City of Seattle 2014; City of New York 2012; City of New York 2013b).

CONCLUSIONS

This study represents an integral step towards understanding the determinants of water consumption in urban multi-family housing. It builds on previous work that has explored the determinants of water consumption on various scales by conducting regression and spatial analyses using actual building water consumption data for New York City. Results of the regression analysis indicate that occupancy, building size, building age, ownership structure (i.e. rental versus ownership), household income and demographic variables all impact the WUI of

multi-family buildings in New York City. Moreover, a statistically significant relationship is observed between WUI and EUI suggesting that coupled water and energy efficiency policies could be effective in encouraging resource consumption reductions in urban buildings. Results of the GWR spatial analysis illustrate the spatial variability that occurs for building characteristics, demographic variables and household income across the study area. The analysis and findings presented here give further support to the potential of targeted measures and incentives segmented and classified by building characteristics and neighborhoods may be effective tools for policymakers seeking to increase water efficiency in urban buildings and to accelerate reductions in resource use at the city scale. As the world continues to urbanize, the need for water and other resource conservation in our cities will continue to rise. Increasing the efficiency of urban buildings through data-driven policymaking represents a valuable opportunity to effectively reduce the strain on urban infrastructure and enhance the long-term sustainability of cities.

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Figure 1. Histogram of Water Use Intensity, Calendar Year 2012, Multi-Family Buildings Only (n=4,893).

Figure 2. Visualization of Water Use Intensity, by Building, Calendar Year 2012, Multi-family Buildings Only (n=4,893)

Table 1. Data Definitions and Sources

Physical Building Characteristics & Variable Name	Definition	Source
Floor Area	Gross Building Floor Area	LL84
Number of Floors	Number of Floors above Grade	PLUTO
Building Age	Year of Construction	PLUTO
Swimming Pool	A Binary Variable Equal to 1 if the Property has a Swimming Pool, and 0 otherwise	LL84
% Non-Residential Space	% of Gross Floor Area for Uses other than Residential	LL84
AV per Square Foot	Total Assessed Value per Square Foot	PLUTO
Number of Residential Units in Building	Total Number of Residential Units in Building (greater of PLUTO or LL84 reported data)	PLUTO/ LL84
Cooperative Ownership	Cooperative Building (yes/no)	PLUTO
Mixed-Use Condominium Ownership	Condominium Building (yes/no)	PLUTO
Occupancy Characteristics		
Number of Occupants per Housing Unit	Estimate of Number of Occupants per Housing Unit, based on Population Estimates from Census Data	Census and LL84
Number of Dishwashers per Housing Unit	Number of Dishwashers per Housing Unit	LL84
Number of Bedrooms per Housing Unit	Mean Number of Bedrooms per Housing Unit	LL84
Energy Use Intensity (log)	Natural Log of Whole Building Weather-Normalized Source Energy Use Intensity (kBtu/sf)	LL84
Socioeconomic Characteristics		
Subsidized Housing	Binary variable equal to 1 if the Property contains Subsidized Housing Units, and 0 otherwise (all market-rate)	LL84
Median Household Income	Median Gross Household Income, 2009	Census
% Female	% Female Population in Block Group	Census
% Senior	% Population Over 65 in Block Group	Census
% Black	% Black Population in Block Group	Census

% Hispanic	% Hispanic Population in Block Group	Census
% Renter	% Renter-Occupied Units in Block Group	Census

Table 2. Results of the Non-Weighted and Weighted Linear Regression Model (statistically significant coefficients are indicated in bold)

				Weighted Regression		
	Num of obs	=	2046	Num of obs	=	2046
	F(24, 2021)	=	27.23	F(24, 1210)	=	25.53
	Prob > F	=	0	Prob > F	=	0
	R-squared	=	0.234	R-squared	=	0.233
	Root MSE	=	0.643	Root MSE	=	0.647
	Coef.	Std. Err.	t	Coef.	Std. Err.	t
Number of Occupants per Housing Unit	0.179***	0.042	4.26	0.184***	0.054	3.42
Number of Bedrooms per Housing Unit	-0.034	0.026	-1.33	-0.053	0.028	-1.88
Floor Area (log)	-0.125***	0.033	-3.79	-0.096***	0.037	-2.59
Median Household Income	-0.160***	0.039	-4.06	-0.204***	0.047	-4.33
% Renter	0.420***	0.108	3.89	0.403***	0.137	2.94
Energy Use Intensity (log)	0.003***	0.000	5.61	0.003***	0.001	4.14
% Female	0.618	0.522	1.18	0.766	0.763	1.00
% Senior	0.401	0.297	1.35	0.361	0.421	0.86
Swimming Pool	0.288***	0.131	2.20	0.268	0.178	1.51
% Non-Residential Space	-0.162	0.277	-0.59	-0.404	0.361	-1.12
Subsidized Housing	0.005	0.051	0.10	-0.009	0.071	-0.12
Number of Floors	0.006	0.003	2.01	0.003	0.003	0.93
Assessed Value per Square Foot	-0.001	0.001	-1.33	-0.001	0.001	-0.93
Year Built between 1910 and 1929	0.254***	0.091	2.80	0.202**	0.094	2.15
Year Built between 1930 and 1949	0.108	0.094	1.14	0.052	0.103	0.51
Year Built between 1950 and 1969	0.323***	0.093	3.49	0.237**	0.098	2.43
Year Built between 1970 and 1989	0.222	0.101	2.20	0.159	0.113	1.41
Year Built after 1990	0.048	0.101	0.47	-0.066	0.117	-0.56
Cooperative Ownership	-0.167***	0.035	-4.71	-0.164***	0.045	-3.63
Mixed-Use Condominium Ownership	-0.143**	0.062	-2.30	-0.079	0.072	-1.09
% Hispanic	0.019	0.093	0.20	-0.110	0.130	-0.85
% Non-Hispanic Black	0.071	0.082	0.85	0.103	0.093	1.10

Number of Residential Units in Building	0.000	0.000	0.57	0.000	0.000	-0.62
Number of Dishwashers per Housing Unit	-0.032	0.040	-0.78	-0.019	0.048	-0.40
Constant	5.606	0.749	7.48	6.084	0.890	6.84

*p < 0.1 **p < 0.05 *** p < 0.01

Table 3. Results of the Geographically Weighted Regression Model

Variable	Min.	1st Qu.	Median	3rd Qu.	Max.
X.Intercept.	3.038	4.846	5.825	6.158	7.775
Number of Occupants per Housing Unit	0.138	0.161	0.215	0.269	0.342
Number of Bedrooms per Housing Unit	-0.078	-0.052	-0.026	-0.013	0.006
Floor Area (log)	-0.167	-0.151	-0.130	-0.117	-0.104
Median Household Income	-0.229	-0.175	-0.148	-0.127	-0.053
Median Household Income	0.385	0.448	0.507	0.537	0.650
Energy Use Intensity (log)	0.002	0.002	0.003	0.003	0.004
% Female	-0.129	0.139	0.404	0.623	0.955
% Senior	0.071	0.240	0.439	0.657	1.139
Swimming Pool	0.265	0.300	0.322	0.354	0.468
% Non-Residential Space	-1.079	-0.523	-0.331	-0.148	0.811
Subsidized Housing	-0.041	-0.015	0.022	0.054	0.160
Number of Floors	-0.003	0.001	0.006	0.007	0.010
Assessed Value per Square Foot	-0.002	-0.001	-0.001	0.000	0.001
Year Built between 1910 and 1929	0.035	0.142	0.234	0.302	0.391
Year Built between 1930 and 1949	-0.096	0.007	0.086	0.157	0.258
Year Built between 1950 and 1969	0.201	0.280	0.310	0.409	0.495
Year Built between 1970 and 1989	-0.053	0.068	0.192	0.294	0.426
Year Built after 1990	-0.342	-0.167	0.004	0.097	0.226
Cooperative Ownership	-0.218	-0.170	-0.155	-0.107	-0.075
Mixed-Use Condominium Ownership	-0.192	-0.146	-0.095	-0.079	-0.043
% Hispanic	-0.256	-0.116	-0.054	0.038	0.137
% Non-Hispanic Black	-0.052	0.027	0.171	0.256	0.356
Number of Residential Units in Building	0.000	0.000	0.000	0.000	0.000
Number of Dishwashers per Housing Un	-0.070	-0.045	-0.030	-0.017	0.019

Figure 3. Plotted coefficient of determination across the study area. Significant spatial differences occur in the explanatory power of the model and thus illustrate the need for accounting for such spatial heterogeneity in the regression analysis.

Figure 4. Mapped GWR Results for Person per Household Occupied, Median Household Income, Percent Population Female, Percent Population Seniors, Percent of Space Non-Multifamily and Percent Renter Occupied.